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An Innovative Remote Sensing Image Retrieval techniques Based on Haar wavelet-LTRP and ANFIS

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Abstract

In the existing Remote sensing image retrieval methods, the images are extracted from the remote sensing image database by means of three characteristic models they are visual features, object features and the scene feature. Although this technique achieves high retrieval accurateness, the precision value is low down. In order to enhance the efficiency and precision value even more higher a Haar wavelet based LTRP technique is proposed in this paper. To extract the object feature instead of earlier new watershed segmentation(NWS) method, Haar wavelet based LTRP technique is used. In the proposed technique, at first the visual features are removed from the images by means of the spatial spectral heterogeneity technique. Afterwards the object features are removed by applying the Haar wavelet and the object features are extracted from the wavelet band by developing LTRP method and the Extracted object features are classified by Neuro-Fuzzy system typically known as ANFIS. Subsequently Scene semantic models are used for the recovery of parallel scene images from the database. The projected RSIR system based on Haar wavelet-LTRP and ANFIS technique are executed in working platform of MATLAB. The performance is measured by utilizing a compilation of remote sensing images taken from the database. In addition the recital is examined by comparing the projected Haar wavelet-LTRP method with the NWSRSIR and the usual SBRSIR method in terms of performance estimate metrics such as precision, recall and F-Measure rate. The implementation effects show the competence of projected Haar wavelet based LTRP method in Remote sensing image retrieval method.

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***Keywords*:Remote Sensing Image Retrieval (RSIR); Local Tetra Pattern (LTRP); Artificial Neural Network Fuzzy Inference System (ANFIS); Scene Semantic (SS).**

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1. Introduction

Image database systems are being made at an ever-increasing rate. An alphanumeric index for images recovery, the usual image databases was used [1]. Though, human beings are not used to recover images based on their alphanumeric indices. In earlier, an integrated feature extraction and object recognition method is being examined by researchers to permit queries on large databases using example images, user-constructed sketches and drawings, colours and texture patterns, and other graphical information [2]. The algorithms and methods being enhanced in such a context have been given the name of content-based image retrieval (CBIR) [3].

Content-based image retrieval (CBIR) technology was projected in 1990s using image vision contents such as texture, spatial relationship, shape, colour not using image entry to explore images [4] [5]. Great movement has been complete in premise and functions in the later stages and so image recovery system is also had an outlook of text-based image retrieval system [7]. This kind of system only recovers scenes based on physical location, spatial characteristic of the imaging instrument, attainment date and etc. [8]. It determines some conventional image retrieval troubles, for example, physical notations for images bring users a large amount of workload and mistaken subjective account. After more than one decade, it has been enhanced as content-based vision information retrieval technology as well as image information and video information [6]. Though, queries cannot course this type of in turn, as the text-based process centres on explore for a scene that shares a parallel ground cover characteristic with certain query scene [9] [10].

2. Related Works

To search the most informative pixels through intelligent sampling with model based heuristics was projected by DevisTuiaet al. [21]. In their technique, a complete hierarchical explanation of the data is given chased by sampling and labeling of pixels. This assisted to determine the data partitioning that best matches with the user's normal classes. Cheng Qiao et al. [22] have enhaced spectral matching concepts and considered spectral and spatial information to initiate adaptive feature extraction method for content remote sensing image retrieval system. In this work, the necessary spectral representation of thematic object was measured through end member selection and then accomplished absolute extraction via "whole-local" scale spectral matching. T. Blaschke [23] has exhibited the implication of object based image analysis; especially geospatial object based image analysis whereas Marco Quartulli et al. [25] have shown the importance of content based image retrieval in earth observation image archives and analyzed the state of the art techniques.

A semantic-based image retrieval in which a one dimensional hidden markov models (HMM) has been designed in terms of 'observation-sequence' and 'observation-density' manipulation approaches was propounded by Brandt Tsoet al. [24]. In 2006, Ruan et al. [26] have proposed an ontology draw close to for semantic-based image rescue in remote sensing archives, however the implication of the semantic features are not well presented in the approach..

In [27], Wang and Song introduced scene semantic (SS) matching for CBIR in remote sensing records. They first mapped the low level image visual features into multilevel spatial semantics through visual features extraction, objected based classification of support vector machines, spatial relationship inference and SS modelling.

3. Proposed remote sensing image retrieval based on Haar Wavelet-LTRP and ANFIS

Rapid growth of remote sensed information makes a new research challenges in processing, transferring, archiving and it builds the image retrieval more difficult. Thus, the major issue of remote sensing image retrieval (RSIR) is to recover the real data stored in a database, information that is germane to a query images according to certain characteristics such as color, texture and shape information relating the image contents. In the projected method, at first the visual features are digging out from the images by means of the spatial spectral heterogeneity technique. Afterward the object features are take out by applying the Haar wavelet and the object features are extracted from the wavelet band by developing LTRP technique and the Extracted object features are classified by Neuro-Fuzzy system typically known as ANFIS. After that Scene semantic models are used for the recovery of similar scene images from the database. The figure 1 shows the block diagram for the RSIR system.

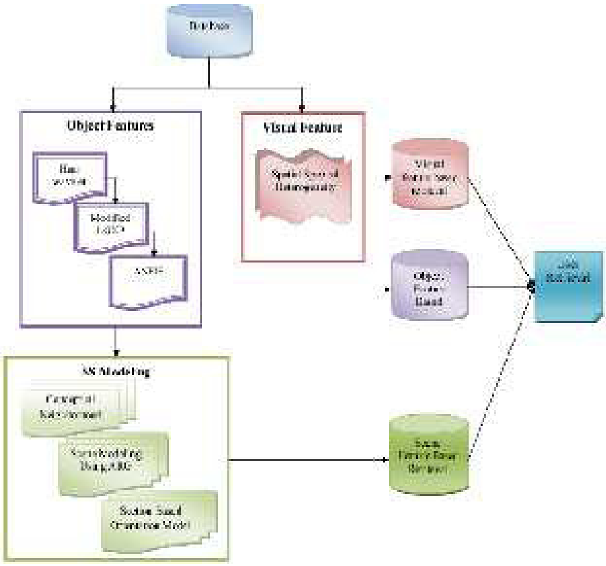


Fig .1. Structure of proposed Remote Sensing image retrieval

$$D_i = \{d_{x1}, d_{x2}, d_{x3}, \cdots d_{xn}\} \; (1)$$

$$Q_j = \{q_{x1}, q_{x2}, q_{x3}, \cdots q_{xm}\} \; (2)$$

Let $D_i : i = 1,2,\cdots n$ be a database imagesand be a query database images where i and j are the number ofimages from the database. q_x be a query image from the database

The imageis considered as the query image and the parallel images like query image are retrieved from the database using the feature extraction methods. Originally the query image visual feature is removed using spatial spectral heterogeneity and the extracted visual feature is denoted as and the resultant images like query images are stored in the database. In second stage the object features are extracted by applying Haar Wavelet on the query image. Thus attained wavelet band is developed by using LTRP method in order to extract the object feature. Thus the attained objects features are trained by Neuro fuzzy classifier (ANFIS).Then SS modelling will applied for the retrieval of similar scene images feature from the database, which is parallel to the query image. The detailed description about this RSIR is described in below sections.

Our proposed system comprised of five stages namely:

i)Visual Feature Extraction

- Spatial spectral heterogeneity

ii)Object Feature Extraction

- Haar Wavelet
- LTRP

iii)Classification

- Neuro Fuzzy (ANFIS)

iv)Scene Feature Extraction

- Scene Semantic (SS) Modeling

v) Retrieval Phase

3.1Visual Feature Extraction Based on Spatial-Spectral Heterogeneity

The images which have the parallel visual features like the query image are extracted by Spatial-Spectral Heterogeneity. The image which has the size of has been taken from the database.
Two features are extracted in visual feature extraction they are as follows:

- color feature
- Texture feature

3.2 Object Feature Extraction Based on Haar-LTRP

The images which have the comparable object features like the query image are extracted by Haar-LTRP. Here the images are focused to object feature extraction. First the Haar wavelet transform is applied and then the object features are extracted from the wavelet band by utilizing the LTRP technique.

3.2.1 Haar Wavelet Transform

Haar wavelet is the easiest type of wavelet which is usually performed for signal and image levelling by considering its “energy compaction” properties, i.e., large values are likely to become larger and small values smaller. One distinctive feature that the Haar alter contains is that it lends itself easily to simple hand calculations, memory proficient and also it is precisely reversible without the edge effects. In the Haar wavelet transform, LL band is the most important band in which object can be extracted more accurately.
Here we apply a one level haar wavelet on images to each row and each column of the resulting image. The resulted image is decomposed into four sub bands LL, HL, LH and HH band (L= Low and H= High). The LL sub band contains the approximation of the original image while the other sub band contains missing details. Hence LL band is the most important band in which object can be extracted more efficiently.

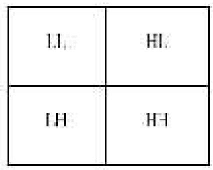


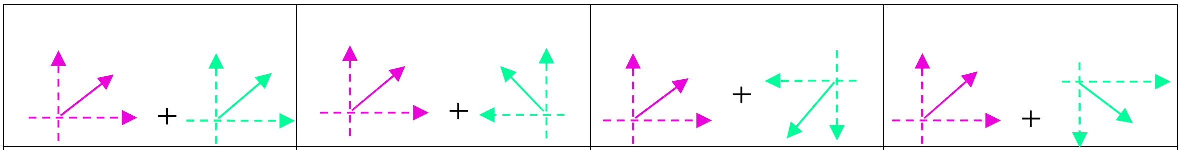
Fig.2 . Four sub bands of one level Haar wavelet

The band obtained from the one level wavelet transform is defined as $b(o_x)$ thus the obtained LL band is exploited in the object feature extraction method.

3.2.2 Local Tetra patterns (LTrP)

In our proposed technique, the object features will be extracted from the obtained image LL band by means of Local tetra pattern (LTrP) technique. Local tetra examples can be competent of extracting the information from images in four directions, so more exhaustive information are extracted by LTrP. In local tetra patterns (LTrP) there are two patterns like tetra and magnitude patterns are calculated by the center pixel and its neighbourhood’s pixel values. . In a given LL band $b(o_x)$, the center pixel value is signified as C_P, and the horizontal and vertical neighborhoods of C_P is represented as C_h and C_v respectively.

Then we apply first-order derivative in horizontal and vertical directions to the neighbourhood pixel. We attain the direction and magnitude of the neighbourhood pixel. If the direction of the center pixel and the direction obtained from the neighbourhood pixel are not same, we assign value to the corresponding bit of the LTrP. based on the condition in fig .3



0	2	3	4

Fig.3 represents the four directions

$$R(C_p) = \{ f(L_{dir}(C_p), L_{dir}(C_1), f(L_{dir}(C_p), L_{dir}(C_2), \cdots f(L_{dir}(C_p), L_{dir}(C_d))\}|_{d=8} \quad (15)$$

$$f(L_{dir}(C_P), L_{dir}(C_d) = \begin{cases} 0, & L_{dir}(C_P) = L_{dir}(C_d) \\ L_{dir}(C_d), & else. \end{cases} \quad (3)$$

From (3) and (4), we get 8-bit tetra pattern for each center pixel. Then, we separate all patterns into three parts based on the direction of center pixel. Finally, the tetra patterns for each part (direction) are converted to three binary patterns. These three binary patterns are obtained as follows

$$R(C_P)|_{dir=2,3,4} = \sum_{d=1}^{D} 2^{(d-1)} * f(R(C_P))\Big|_{dir=2,3,4} \quad (4)$$

$$f(R(C_p))\Big|_{dir=\theta} = \begin{cases} 1, & if\ s(p_c) = \theta \\ 0, & else \end{cases} \quad (5)$$

3.3 Classification using ANFIS

The object characteristics acquired from the LTRP are classified using the well known classifier named ANFIS which contains five layers of nodes. Out of five layers, the first and the fourth layers possess adaptive nodes whereas the second, third and fifth layers possess fixed nodes. The structure of ANFIS having five layered feed-forward neural network is shown in figure 4. In both ANN and FL, the inputs are given to the input layer (as input membership function) and the output is obtained from the output layer (as output membership functions). The architecture of the ANFIS is given in figure 4.

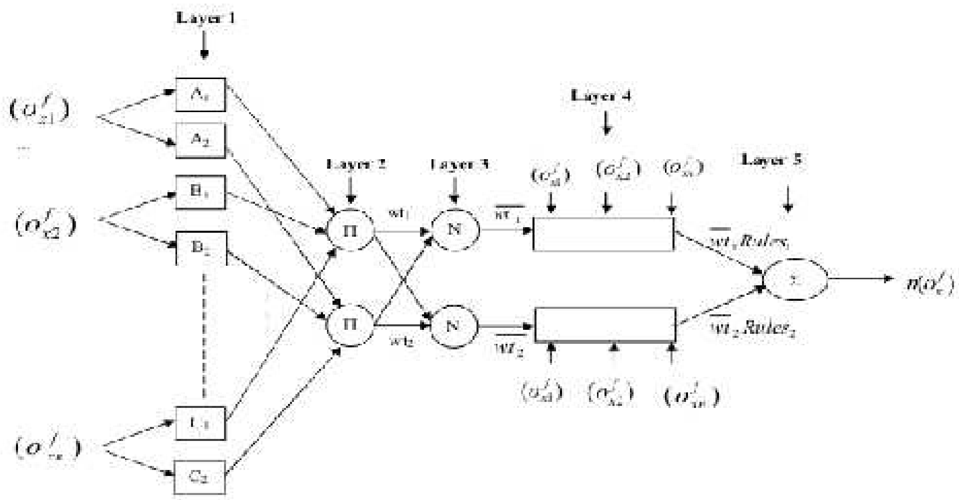


Fig.4 Architecture of ANFIS

3.4. Feature Extraction Using Scene Semantic (SS) Modeling

Scene semantic models are used for the repossession of similar scene images like query image from the database. The object features acquired using the LTRP-ANFIS method was subjected to Scene Feature Extraction using SS modelling. Here three models are computed they are as follows:

- Conceptual neighborhood Model.
- Section- based orientation model.
- Scene modeling using ARG

3.5Retrieval Phase

The parallel query images from the database have been repossessed by via this visual aspect extraction, Object feature extraction and the scene feature extraction. By using the SS matching modelling we are retrieving the parallel query images. For that Q is consider as the query image and the T is consider as the objective image. The objects in the query images must be less than that of the target image. Below table 1 shows the matching scheme of each category and figure 5 shows the stratified graph. The '1', '2', '3', '4', '5', '6' are the sub category of that of the elements I, II, III, 1V. Example: Let us consider category I is the Water body, in that contain the objects river and sea that which are represented in '1' and '2' respectively.

Table I: Matching Scheme

Category	Q	T	Matching pattern based on category level
I	1, 2	2, 5	$1 \leftrightarrow 2, 2 \leftrightarrow 5$ *or* $1 \leftrightarrow 5, 2 \leftrightarrow 2$
II	3, 4	1, 6	$3 \leftrightarrow 1, 4 \leftrightarrow 6$ *or* $4 \leftrightarrow 1, 3 \leftrightarrow 6$
III	5	3	$5 \leftrightarrow 3$
IV	6	4	$6 \leftrightarrow 4$

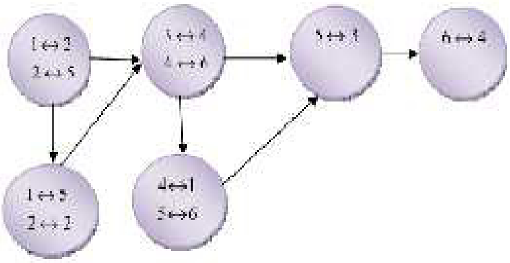


Fig.5.stratified graph

4. Experimental Results and Discussion

The proposed LTRP-ANFIS based Remote Sensing image retrieval was implemented in the working platform of MATLAB (version 7.12) with machine configuration as follows:
Processor: Intel core i7
CPU Speed: 3.20 GHz,OS: Windows 7,RAM: 4GB

In the projected technique, originally the visual features are extracted from the images using the spatial spectral heterogeneity technique. Afterward the object features are extracted by applying haar wavelet and the wavelet band is developed by LTRP technique and that extracted object features are classified by the Neuro fuzzy method. Then the similar scene images from the database are extracted by the SS modelling. A more number of remote sensing images are utilized in the performance assessment method. Figure 6: shows the original remote sensing images which are shown in below.

Fig.6.Original Remote Sensing Images

The above shown original remote sensing images are utilized in the concert analysis of projected remote sensing image recovery method. In our proposed work, the images are classified into four areas namely, water body, metro area, Forest and Desert From these remote sensing images three features such as visual, object and ss modelling are retrieved. The descriptions which are parallel to the query scenes are extracted and stored. Also Based on the features stored in the databases the images are retrieved based on the query images. The retrieved images are shown below in figure.7

(i)

(ii)

(iii)

(iv)

Fig.7.Retrieved Results (i) Query Image (ii) VF based extracted images (iii) OS based extracted images (iv) SS based retrieved images

3.5 Retrieval Phase

Our proposed LTRP-ANFIS based RSIR system performance is examined by the statistical measures such as Precision, Recall and F-Measure.

The performance is assessed by three quantitative performance metrics namely,

F-measure,
precision,
Recall

Discussion:

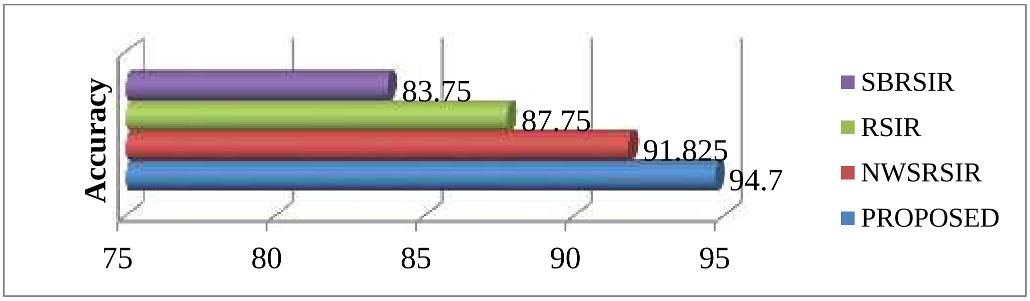
Performance assessment is done for LTRP-ANFIS method The evaluation metrics has been calculated for visual feature, object feature and scene semantic features. For the four several remote sensing image areas namely, water body, metro area, Forest and Desert. Precision is one of the important performance measures in image retrieval process. From the above table 3 to 4, we can scrutinize that the precision rate and recall rate of the proposed method is higher than the other techniques. Similarly, f-measure is also higher than the other techniques. Even though the difference is small, it indicates the enhancement in the performance of the proposed technique. In addition in comparative analysis our proposed LTRP-ANFIS based retrieval performance is compared with the existing technique such as NWSRSIR, RSIR and SBRSIR Classification Results for Coastal, metro area, Forest, Desert images and the performance table has been given below.

Table 1: Performance of Our Proposed LTRP-ANFIS and the existing system such as NWSRSIR, RSIR and SBRSIR Classification Results for Coastal, metro area, Forest, Desert images.

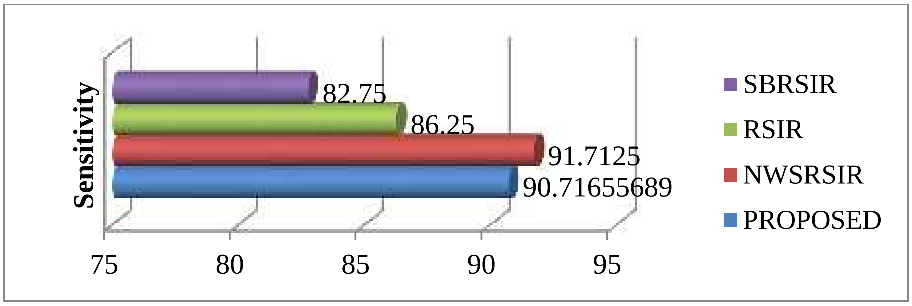
Measures	PROPOSED	Proposed NWSRSIR	RSIR	SBRSIR
Accuracy	94.7	91.825	87.75	83.75
Sensitivity	90.7166	91.7125	86.25	82.75
Specificity	95.9073	91.875	83.75	83.5
FPR	4.0927	3.475	5.25	5
PPV	87.4	91.5	85.75	80.75
NPV	97.1333	89.875	86	78.8
FDR	1.26	1	4.5	4.5
MCC	85.5606	81.825	52.675	61.7

Discussion:

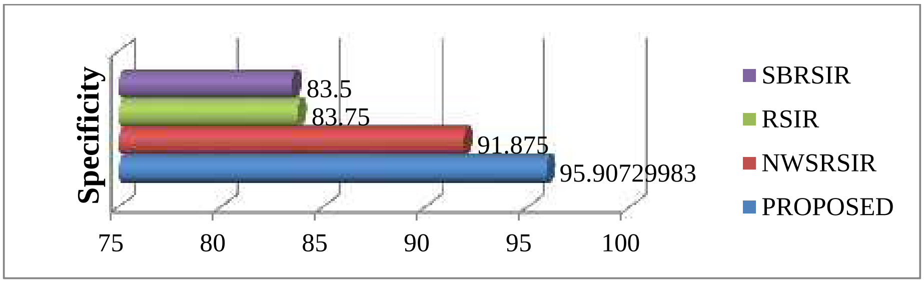
Table 1 shows the performance of our proposed LTRP-ANFIS technique and the existing system such as NWSRSIR, RSIR and SBRSIR in terms of Accuracy, sensitivity and specificity measures. The efficiency of our proposed technique is (94.7%) but the existing technique NWSRSIR, RSIR and SBRSIR offers only (91.82%), (87.75%) and (83.75) of accuracy respectively. similarly the specificity of our proposed method (95.90%)but the existing technique offers (91.87%),(83.75%) and (83.5%) respectively. in case of sensitivity our proposed technique produce (90.71%) it is probably low when compare to NWSRSIR. Even though the sensitivity of our proposed technique is lower than the existing NWSRSIR it not much vary and certainly higher when compared to other existing RSIR and SBRSIR techniques. And also When compared to the other techniques the proposed technique has higher rate of precision recall and f-measure. Hence our proposed method provides better performance results. The performance of proposed and existing methods comparison graph is illustrated in fig. 8.



(i)



(ii)



(iii)

Fig.8. Performance of Our Proposed LTRP-ANFIS and the existing NWSRSIR, RSIR and SBRSIR system. For the water body, metro area, Forest, Desert images in terms of i) accuracy ii) sensitivity and iii) specificity

Discussion:

Figure 8 demonstrate the Performance of Our Proposed LTRP-ANFIS based RSIR and the existing RSIR and SBRSIR system. For the water body, metro area, Forest, Desert images in terms of accurateness, sensitivity and specificity. From the graph it has been shown that the exactness of the suggested technique is (94.7%) While Existing methods such as NWSRSIR RSIR and SBRSIR offers only 91.87%),(83.75%) and (83.5%) of accuracy correspondingly. When compared to the existing systems, the proposed LTRP-ANFIS has given higher correctness rate. It symbolizes the optional method is capable than the other methods. Hence our proposed method provides better performance results.

5. Conclusion

In this paper we have conscious to suggest an efficient LTRP-ANFIS based remote sensing Image Retrieval (SFIR) system using LTRP-ANFIS method so as to minimize the shortcoming in the earlier technique. Moreover, in comparative testing, our proposed technique performance is compared with the existing method. The proposed technique has elevated precision rate and F-Measure than the other techniques such as NWSRSIR, RSIR and SBRSIR. The comparison result shows that our proposed LTRP-ANFIS based remote sensing Image Retrieval (RSIR) technique retrieved the Images more accurately than the existing methods. Hence, it is proved that our proposed methods system using LTRP-ANFIS technique more precisely and efficiently retrieves the images by accomplishing higher retrieval rate..

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